A Study of Determinants of Generative AI Adoption among University Faculty Members in India: An Extended UTAUT Model Integrating Trust and Privacy

A

SYNOPSIS

(THESIS PROPOSAL)

SUBMITTED TO

THE ICFAI University Dehradun

IN PARTIAL FULFILLMENT OF THE REQUIREMENT

FOR THE AWARD OF THE DEGREE OF

DOCTOR OF PHILOSOPHY (Ph.D.)

IN

MANAGEMENT

BY

Perugupalli Alekhya

(Enrollment No: RSIBS242008)

Under the Supervision of

Dr. Puneet Kumar Gupta
Associate Professor

ICFAI Business School
The ICFAI University, Dehradun
March, 2026

The ICFAI University, Dehradun

Candidate's Declaration

I, **Perugupalli Alekhya**, declare that the synopsis entitled, ***"A Study of Determinants of Generative AI Adoption among University Faculty Members in India: An Extended UTAUT Model Integrating Trust and Privacy"*** being submitted in partial fulfillment of the requirement for the award of the degree of Doctor of Philosophy in *MANAGEMENT* under ICFAI Business School, The ICFAI University, Dehradun during the academic year 2025-26.

It is the work that is expected to be carried out under the supervision of Dr. Puneet Kumar Gupta, Associate Professor, ICFAI Business School. It is further declared that the synopsis is within the plagiarism limit and copy of the same is attached as per the University norms.

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(Perugupalli Alekhya)

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CERTIFICATE

This is to certify that the thesis entitled, *"A Study of Determinants of Generative AI Adoption among University Faculty Members in India: An Extended UTAUT Model Integrating Trust and Privacy"* is an original piece of work done by ***Perugupalli Alekhya*** under our supervision being submitted in the partial fulfillment of the requirement for the award of the degree of Doctor of Philosophy in ***Management*** under ICFAI Business School, The ICFAI University, Dehradun during the academic year 2025-26.

Further, it is certified that the synopsis is within the plagiarism limit and copy of the same is attached as per the University norms.

16.03.2026

Signature of the Supervisor in full

Name in Capital Letters

Dr. PUNEET KUMAR GUPTA

Associate Professor

ICFAI Business School

The ICFAI University, Dehradun

ICFAI UNIVERSITY DEHRADUN

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Author Name	Perugupalli Alekhya
Course of Study	Ph.D. (Management)
Name of Guide	Dr. Puneet Kumar Gupta
Department	ICFAI Business School
Acceptable Maximum Limit	10
Submitted By	research@iudehradun.edu.in
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ABSTRACT

The rapid advancement of Generative Artificial Intelligence (GenAI) has created new opportunities and challenges for higher education institutions, particularly for faculty members who are increasingly required to integrate AI-enabled technologies into teaching, research, and academic decision-making. The Indian university system presents a unique context characterized by institutional diversity, varying levels of digital readiness, and evolving policy expectations under NEP 2020. Despite the growing relevance of Generative AI, empirical evidence on its adoption among faculty members in India remains limited. Moreover, existing technology adoption studies have largely focused on students or users in developed economies, with insufficient attention to faculty members operating within diverse and resource-constrained institutional contexts.

Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), the present study proposes an extended UTAUT model by integrating Trust and Privacy to examine the determinants of behavioural intention and use behaviour towards Generative AI adoption among university faculty members in India. The study adopts a quantitative, explanatory research design, using a structured questionnaire to collect data from faculty members working in universities across India. Structural Equation Modeling (SEM) will be employed to test the proposed relationships among the constructs.

By extending the UTAUT framework and focusing on faculty members as key organizational stakeholders, the study aims to contribute to the literature on Generative AI adoption in emerging economies and provide practical insights for institutional leaders and policymakers to support responsible and effective adoption of Generative AI in higher education.

Keywords: *GenAI Adoption; UTAUT, VAM, Trust, Privacy, SEM*

1. Introduction

The proliferation of disruptive technologies since past few decades has marked exponential growth trajectory. It is matter of curiosity and research that few innovations have marked swift and widespread acceptance, but many others failed to get expected attention from the users (Rogers, 1962; Davis, 1989; Venkatesh et al., 2003). To remove disparity, a section of Information system researchers mostly focuses on understanding factors affecting the individuals to adopt or reject a new technology, which is key for policymakers, developers, and institutions, as to anticipate societal needs so as to design solutions that are more likely to be accepted by the users' (Venkatesh et al., 2003; Dwivedi et al., 2019).

Liu et al. (2019) defined technology adoption as the decision-making process through which the users ascertain whether to integrate a new technology into their day-to-day life. Conversely, technology acceptance relates to the changes in users' attitude, cognition, and behaviour that may alter a user's inclination to try and continue using a new technology (Van Biljon & Kotzé, 2008).

Past researchers have developed various theories and models as to get insights about factors shaping users' behavioural intentions and actual use behaviours. Though several technology adoption theories have been developed, some of the most prominent models include the Technology Acceptance Model (TAM) (Davis, 1989), which determines perceived usefulness and ease of use as the important determinants of attitude towards behavioural intention to adopt technology; the Diffusion of Innovations Theory (IDT) (Rogers, 1962), which centres around determinants such as relative advantage of using a new technology and its compatibility; the Theory of Planned Behavior (TPB) (Ajzen, 1991), which includes attitudes, subjective norms, and perceived behavioural control as core to adoption; and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which condenses eight core models to predict behaviour intentions and actual usage across diverse technology settings.

The higher education sector worldwide is undergoing significant transformation in the way information systems (IS) are utilised to conceptualize, deliver, and administer academic activities (Popenici & Kerr, 2017; Hwang et al., 2020). Artificial Intelligence (AI) has catalyst this digital transformation by aiding personalized learning experiences, imparting intelligent tutoring facility, timely automated assessment, accessing virtual laboratories, and data driven academic decision

making (Chen et al., 2020; Pedro et al., 2019; Khosravi et al., 2022). Remarkably, a recent study by Johnston et al. (2024) conducted across Asia Pacific region reveals a rapid increase in awareness with generative AI (Gen AI) tools, while Indian students and employees reported higher usage of GenAI and were found to be optimistic about their potential economic and career benefits. The significant increase in GenAI platforms provides significant opportunity and research motivation in the area of adoption of GenAI in higher education sectors (Dwivedi et al., 2021; Wang, 2020).

Generative AI tools have significantly increased the capabilities of various traditional learning technologies, such as support for the online libraries and Learning Management Systems (LMS), allowing interactive content generation, enabling automated feedback, and more importantly, providing academic assistance in a intelligent way (Rahman & Watanobe, 2023; Fuchs, 2023). Behaviour of Generative AI tools just like a human mind eases prompt responses, supports translation and refinement of languages, facilitates assessments of the students, and provides interactivity and learning at scale (Adiguzel et al., 2023; Atlas, 2023; Huang et al., 2021). Previous research related to higher education revealed that these innovations will continue to improve instructional efficiency, balancing the teaching load of the instructor, and individualized feedback, consequently, will improve not only the teachers but the teachers as well as students in terms of their effectiveness (Rahman & Watanobe, 2023; Chen et al., 2020). Nevertheless, scholars, teachers and experts have great concern regarding academic integrity, diminishing critical thinking of the users, significant enhancement in plagiarism and AI contents, technical factors such as bias in the algorithms, and moreover dependability of the user toward AI (Cotton et al., 2023; Baker & Hawn, 2022; Saheb & Saheb, 2021; Perrotta & Selwyn, 2020) and therefore the lack of awareness about the determinants influencing adoption of generative AI by faculty members of is detrimental for the body of knowledge (Dakakni & Safa, 2023; Dwivedi et al., 2021).

Most empirical studies on AI adoption in higher education have primarily focused on students, general AI tools, or mixed sampling comprising students, teachers, and researchers in underdeveloped countries (Nye, 2015; Luan et al., 2020; Su et al., 2022). For instance, a recent study in Bangladesh applied an extended UTAUT framework, incorporating factors like trust and privacy, to examine AI adoption for academic purposes. Rana et al. (2024) concluded that users' performance expectancy, their effort expectancy, social influence, and users' trust on technology

had shown positive impact on users' behavioural intention to adopt new technology, while users' concerns regarding compromise in individuals' privacy negatively influenced their intention to adopt new technology.

The generative AI tools such as ChatGPT, Gemini, and similar platforms are increasingly being used for academic activities in Indian universities, including lecture preparation, teaching material development, assessment support, language translation, and research assistance (Rahman & Watanobe, 2023; Dwivedi et al., 2023). Though the Generative AI adoption is the emerging research field, there remains a paucity of quantitative investigations examining the factors influencing university faculty members' behavioural intention and use behaviour towards Generative AI adoption in India. Most of the past researchers focused on students' approach towards acceptance or adoption of AI tools or limited themselves by exploring only the instructive and ethical consequences in a theoretical manner, while negligible numbers of studies providing quantitative or qualitative analyses of faculty adoption dynamics (Kizilcec, 2023; Chen et al., 2020).

2. Literature Review

A two-stage literature review was undertaken. In the first stage, a literature search was conducted to reflect deeply on the various concepts and constructs captured in current literature and review of various theories and models of technology acceptance and adoption. The second phase of the literature review was conducted by levelled extraction and review of the publications pertaining only to Generative AI adoption in higher education institutions.

2.1. Literature Review (Phase-1)

To understand core concepts in literature, this stage involved a thorough review of technology adoption theories. Over the past 45 years, frameworks explaining how individuals adopt new technologies have evolved significantly. Below is a summary of this development:

2.1.1 Theory of Reasonable Action (1975)

According to this mathematical model and the cognitive theory upon which this model is based, the `Attitude" towards a person seems to be the most important determinant of their `Behavioral

Intention". Here “belief” is one’s model of the probability that some action would lead to some outcome or consequences. What each person has ”on Brink” is his or her own positive or negative estimation of a specific behavior or outcome. A person’s ‘intention’ is one’ s own decision to behave, in a certain way based on its belief and an attitude (Fishbein, 1975)

2.1.2 Technology Acceptance Model(TAM) (1986)

TAM—technology acceptance model— TAM is a research paradigm used in information systems that logically explains how and why people accept or intend to use new technology. It involves three key components: Perceived Ease of Use (PEU), Perceived Usefulness (PU) and Attitude toward new technology. PEU indicates to what extent consumers believe that they can use new technologies, while PU expresses their perception for the usefulness of a technology and how it would affect performance. Both PEU and PU determine the attitude, which in turn influences behavioural intention (BI) to use the technology, and finally its acceptance (Davis F. D., 1986).

2.1.3 Theory of Planned Behavior (TPB) (1991)

TPB extends TRA and is used to predict and explain human behavior. It focuses on “Behavioral Intention” and this latter’s “Predictive Power.” Behavioral intention is determined by attitude, subjective norms (influence of family, friends etc), and perceived behavior control (ease or difficulty to perform the behaviour). These factors are believed to combine and form an intention, which then is used to predict whether the intention is likely to result in a given behavior (Ajzen, 1991).

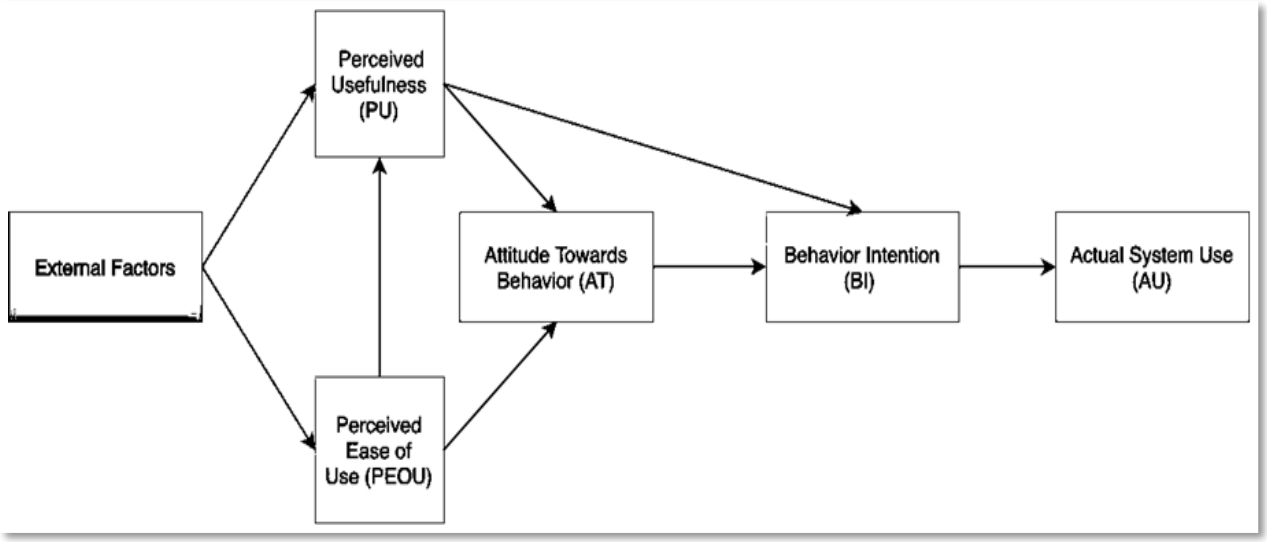


Figure 2.1 – TAM extracted from (Davis F. D., 1986)

2.1.4 Theory of 'diffusion of innovation' (1995)

The "diffusion of innovation" examines how new ideas are accepted and adopted within social systems. Rogers synthesized over 500 studies on this topic, identifying key stages in adoption: understanding, decision-making, persuasion, implementation, and confirmation (Rogers, 1995).

2.1.5 Decomposed Theory of Planned Behavior

The basis of the widely referenced Decomposed Theory of Planned Behaviours (DTPB) was established by Taylor and Todd in 1995, extending the original model by breaking down "Attitude", "Subjective Norms" and PBC into more fine-grained dimensions [3]. What we think will happen and how we think it will be evaluated plays a part in whether we have a favorable attitude toward adopting new technology (Taylor & Todd, 1995).

Social influence describes how people affect the behavior, opinions or attitudes of others. Self-efficacy and external constraints directly influence perceived control of our behaviour; self-efficacy constitutes confidence in executing a certain action, while external constraints are barriers or aids.

2.1.6 Technology Acceptance Model (TAM-2)

Technology Acceptance Model 2 (TAM2), created by Venkatesh & Davis (2000), extends on the original TAM by adding additional outside variables that affect users' intentions to use new technology. The subjective norm, which is defined as the influence of society and peers on an individual, was found to be a significant factor towards acceptance. The degree to which technology affects an individual's reputation at work) is another key determinant of behaviour regarding acceptance. Job relevance indicates how technology is related to job tasks, while output quality refers to how effective the technology was believed to be. Result demonstrability points to the significant influence of tangible rewards on perceived usefulness. Additionally, user experience

2.1.7 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) in 2003. He studied many ideas about how people accept and use technology. UTAUT joins different ideas about technology use. These ideas are the Theory of Reasoned Action (TRA),

Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Motivational Model (MM), Social Cognitive Theory (SCT), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and a mix of TAM and TPB. The model shows four main things that affect if people want to use technology. These are Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Assisting Conditions (FC). Performance Expectancy depends on how useful people think technology is, if it helps with work, and what they expect to get from it. Effort Expectancy means how easy or hard technology is to use. Social Influence means how other people affect your choice. Assisting Conditions are the things that help you use the technology. The model also looks at how things like if you use the technology by choice, your gender, your age, and your experience change these effects. The study found that Behavioral Intention (BI) and Assisting Conditions (FC) influence if you use the technology. Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) affect your intention to use it. Social Influence does not change if you use technology by choice.

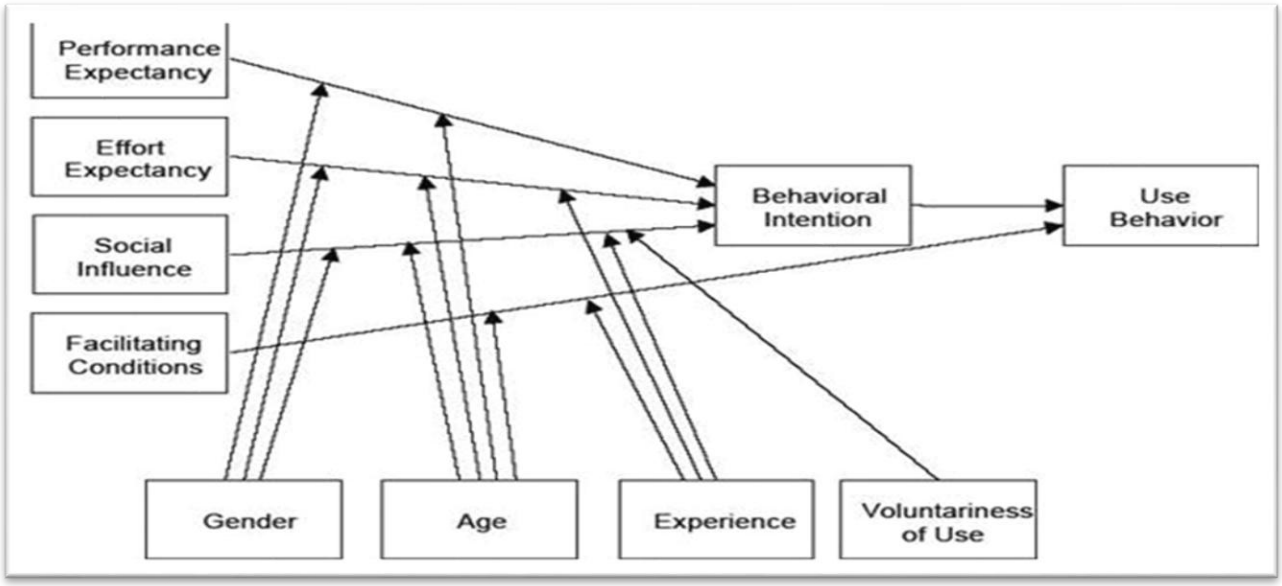


Figure 2.2 - UTAUT Model extracted from (Venkatesh V. M., 2003)

2.1.8 Value-based Adoption Model (VAM)

Kim (2007) studied how people decide to use Mobile Internet. The study uses ideas from economics and marketing about how people choose. It sees new users as both users of technology

and buyers of services. Each user pays the cost to start using it. The study says people pick what gives them the most benefit. They think about the cost and what they get in return. Benefits include how useful and fun the service seems. Costs include how hard it is to use and how much it costs to pay. Figure 2.3 shows this simple model.

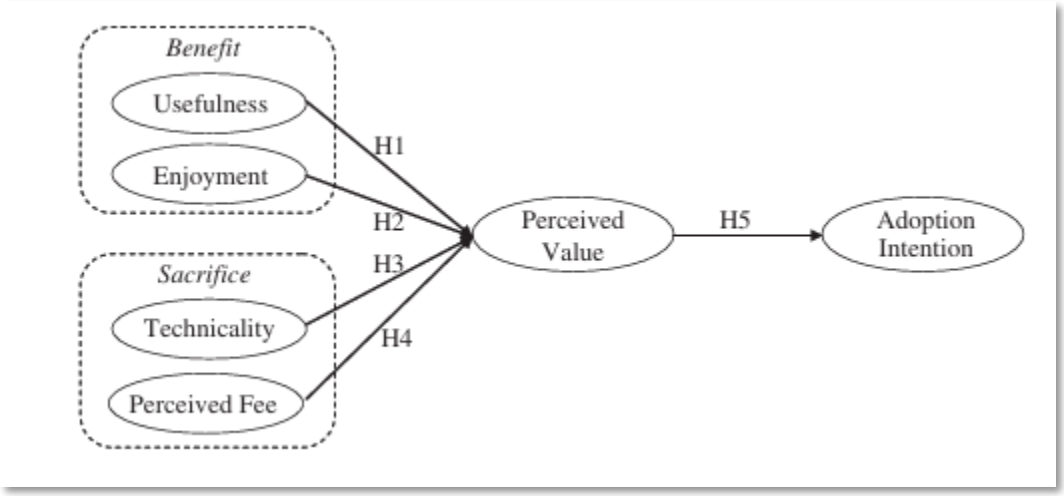


Figure 2.3 Value-based adoption model extracted from (Kim, 2007)

2.1.9 Technology Acceptance Model (TAM-3)

Venkatesh and Bala made TAM 3 in 2008. They joined TAM 2 and the factors that affect how easy a system is to use. The model has three parts. First, there are outside things like system design. Second, there are mental reactions like how useful and easy to use the system seems. Third, there are feelings like attitude or plans to use the system. In TAM 3, "Experience" and "Voluntariness" change how ease of use, usefulness, computer fear, and plans to use relate. The model was tested and works with real IT systems.

2.1.10 Unified Theory of Acceptance and Use of Technology (UTAUT2)

UTAUT looked at workers. UTAUT2 (Venkatesh V. T., 2012) looked at buyers. UTAUT2 focused on practical value. It added three new personal factors: Habits, Fun, and Price. Age, gender, and experience changed how these factors affected what people planned to do and how they used technology. UTAUT2 explained more about what people planned to do, going from 56% to 74%. It also explained more about how people used technology, going from 40% to 52%.

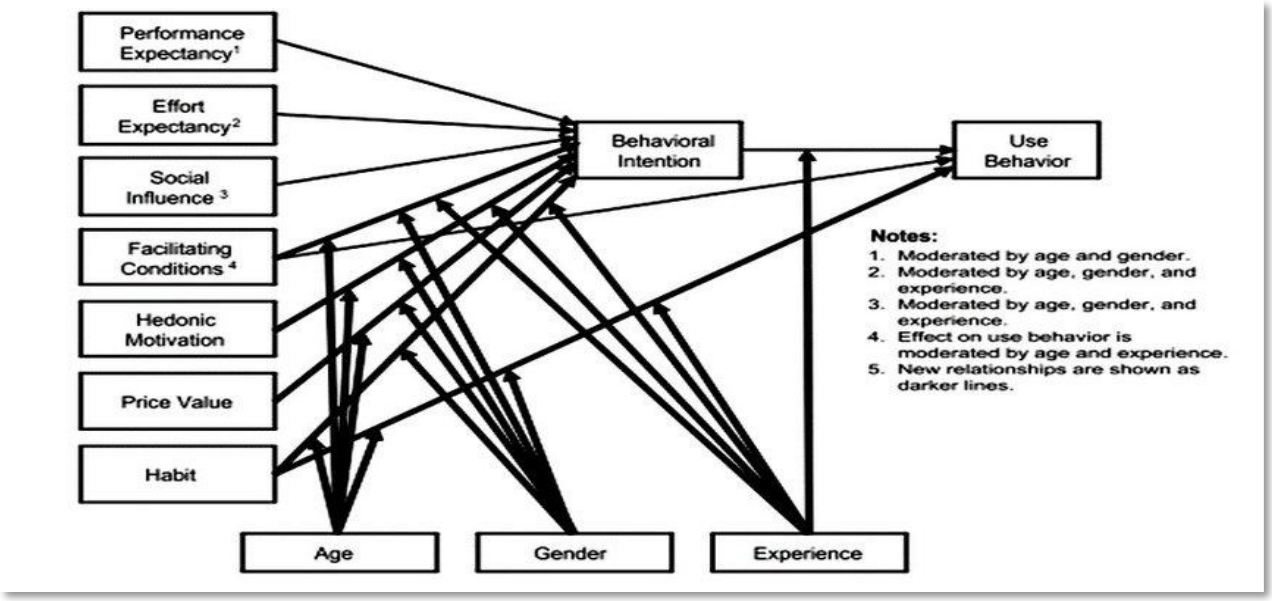


Figure 2.4 – UTAUT-2 Model extracted from (Venkatesh V. T., 2012)

2.1.11 Unified Theory of Acceptance and Use of Technology (UTAUT3)

Farooq (2017) added personal innovativeness (PI) to UTAUT2. He tested it using a simple method called partial least squares structural equation modeling. The study showed that PI affects how people use technology in IT, especially in developing countries. The study also showed that the original UTAUT2 parts—performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit—are important for using new tools like lecture capture systems.

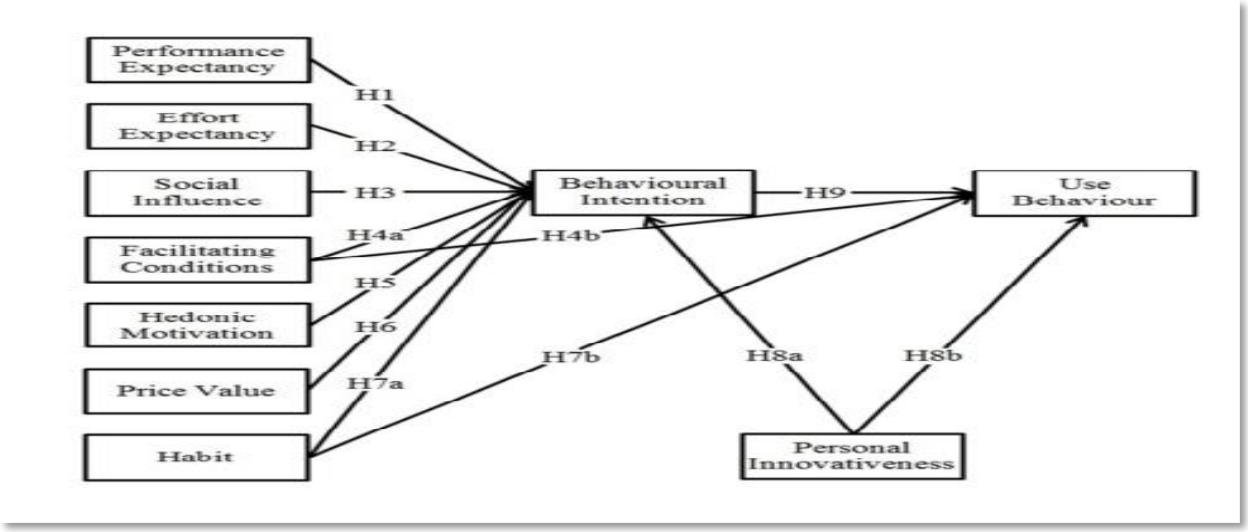


Figure 2.5 – UTAUT-3 Model extracted from (Farooq, 2017)

Table 2.1: Transformation in Information System Adoption Model Research

S. No	Model/Theory	Description/Constructs
1	Theory of Reasoned Action (TRA) (Fishbein, 1975)	Attitude and Subjective Norms are important factors; personal factors in focus.
2	Theory of Interpersonal Behavior (TIB) (Triandis, 1977)	Attitudes, personal beliefs, and social factors are significant; TRA expanded by adding social factors.
3	Expectation-Confirmation Theory (ECT) (Oliver, 1980)	Customers' intention to purchase is influenced by satisfaction from prior use; prior usage is the only personal factor considered.
4	Technology Acceptance Model (TAM) (Davis F. D., 1986)	Perceived usefulness and perceived ease of use determine intention to adopt; extrinsic technological factors emphasized.
5	Social Cognitive Theory (Bandura, 1986)	Personal factors and environmental influences affect behavior; TIB combined with environmental influences (observed reinforcement of others' behavior).
6	Theory of Planned Behavior (TPB) (Ajzen, 1991)	Attitude, subjective norms, and perceived behavioral control; TRA enriched with perceived behavioral control factors.
7	Perceived Characteristics of Innovating (Moore, 1991)	Voluntariness, relative advantage, compatibility, image, ease of use, result demonstrability, visibility, trialability; technology factors such as trialability, observability, complexity, perceived risk.
8	Model of PC Utilization (MPCU) (Thompson, 1991)	Affect, social norms, habits, expected consequences, and facilitating conditions; drawn from TRA and TPB, focuses on actual behavior rather than intention.
9	Motivational Model (Davis F. D., 1992)	Playfulness and enjoyment influence intrinsic motivation; usefulness, ease of use, and subjective norm as extrinsic motivation; intrinsic motivation factored into TAM-1.

10	Igbaria's Model (Iqbaria, 1994)	Perceived fun and perceived usefulness are key determinants; perceived fun replaces perceived ease of use of TAM-1.
11	Decomposed Theory of Planned Behavior (Taylor & Todd, 1995)	Decomposes attitude, subjective norms, and control beliefs into compatibility, ease of use, usefulness, prior experience, reference groups, self-efficacy, and facilitating conditions.
12	Theory of Diffusion of Innovation (Rogers, 1995)	Five stages (knowledge, persuasion, decision, implementation, confirmation) and five adopter categories; applicable in organizational settings.
13	Information System Success Model (DeLone, 1995)	System, information, and service quality, user satisfaction, and net benefits; focuses mainly on technical factors.
14	Task Technology Fit (TTF) (Goodhue, 1995)	Task and technology characteristics, task–technology fit, and performance impacts; focuses on aligning technology with task for actual use.
15	Combined Model of TPB and TAM (Taylor & Todd, 1995)	TPB merged with perceived usefulness and ease of use from TAM; technological and personal factors merged.
16	TAM-2 (Venkatesh & Davis, 2000)	Adds subjective norms, voluntariness, image, job relevance, output quality, result demonstrability; experience and voluntariness as moderators, tested in longitudinal studies.
17	UTAUT (Venkatesh et al., 2003)	Performance expectancy, effort expectancy, social influence, facilitating conditions; integrates 8 models, focuses on extrinsic motivators, explains 56% variance in BI and 40% in use.
18	TPACK Framework (Mishra, 2006)	CK, PK, TK and their intersections (TCK, TPK, PCK, TPACK); applicable to teaching–learning, focuses on teacher knowledge factors, complex so fewer empirical studies.
19	Value-based Adoption Model (VAM) (Kim, 2007)	Usefulness and enjoyment as benefits, technicality and perceived fee as sacrifice; explains adoption via value maximization.

20	TAM-3 (Venkatesh & Bala, 2008)	Explains usefulness and ease of use with self-efficacy, external control, anxiety, playfulness; extends TAM-2, shifts from social to personal (anxiety) influences.
21	Uses and Gratification Theory (Grellhesl, 2012)	Motivations, usage, and gratifications/satisfaction; focuses on intrinsic motivational factors.
22	UTAUT-2 (Venkatesh et al., 2016)	Adds habit, hedonic motivation, price value; includes moderators (age, gender, experience, voluntariness) and accounts for 74% variance in BI and 52% in use.
23	UTAUT-3 (Farooq, 2017)	Introduces personal innovativeness as determinant of BI and use; explains 58% of BI and 68.2% of use, improving over UTAUT-2.

2.2. Phase-II of Literature Review

In Phase II, the author did a Systematic Literature Review (SLR). The author then looked at all papers in the Web of Science (WOS) and Scopus databases. The author then studied theses from Shodhganga. Shodhganga is a place where PhD theses from Indian Universities are kept. Scopus and Web of Science are well-known databases. The author uses these databases to find many journals. This helps researchers to trust the information received. Researchers use these databases to find what is missing in current knowledge. They also use them to see how research changes over time. This keeps their work trustworthy to others. On September 09, 2025, the author searched Scopus and Web of Science for articles. The author used these keywords: ((“theor*" OR "Model") AND ("Chatbot*" OR "ChatGPT" OR "GenAI*" OR "Generative AI*") AND ("Adoption" OR "Acceptance") AND ("Higher Education*" OR "HEIs" OR "Universit*")) The author found 971 articles in Scopus and 721 in Web of Science (Figure 2.6 and 2.7) and **“The preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA)”** flow chart is shown in Figure 2.8.

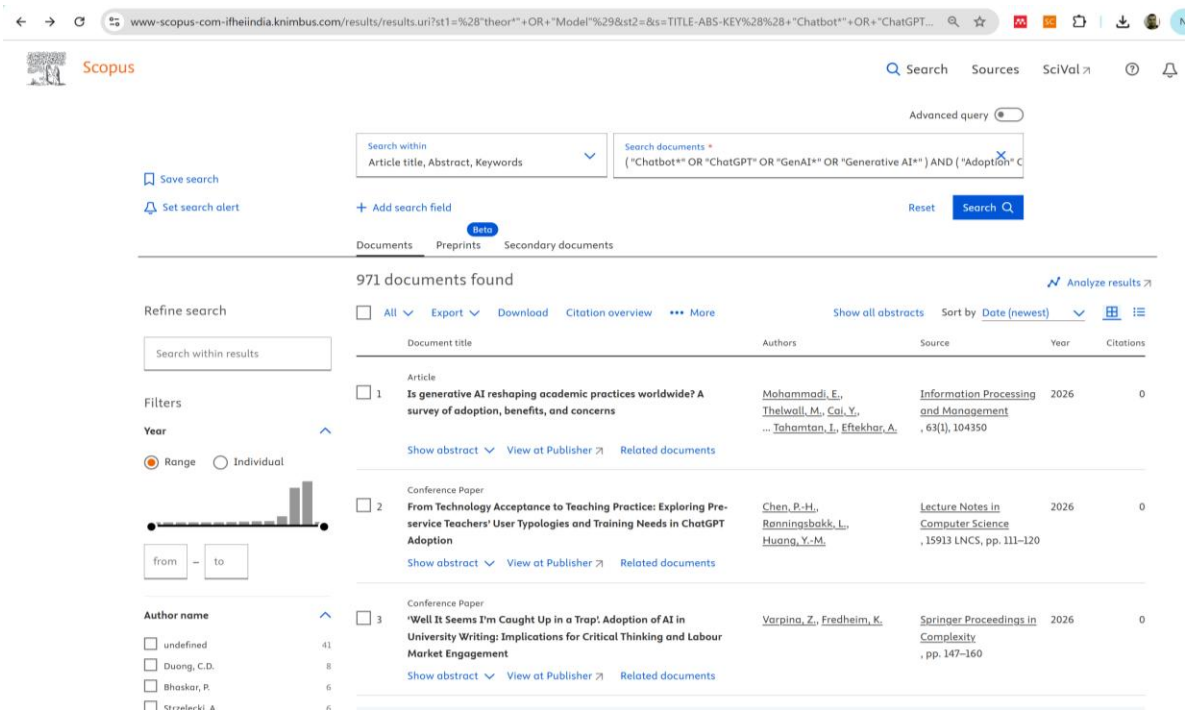
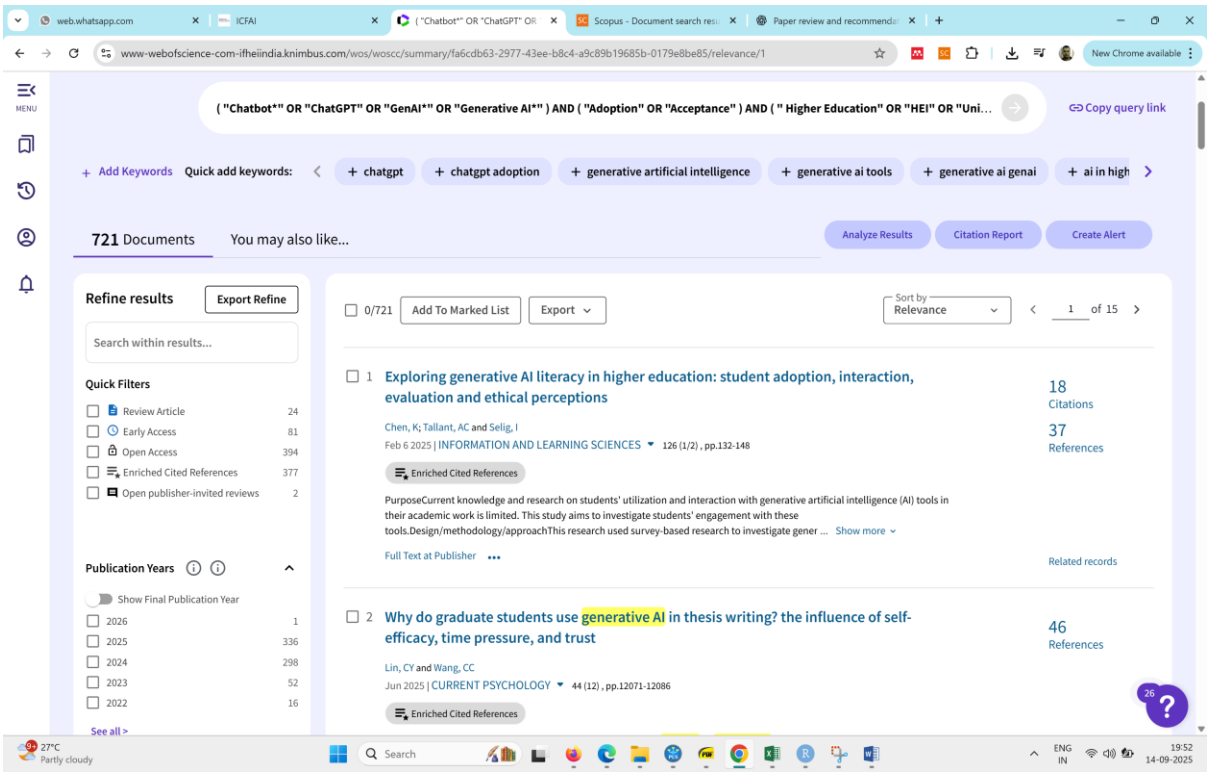


Figure 2.6: Query Results from Scopus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Review Article 24
Early Access 81
Open Access 394
Enriched Cited References 377
Open publisher-invited reviews 2
Publication Years
Show Final Publication Year
2026 1
2025 336
2024 298
2023 52
2022 16
See all >
0/721
Add To Marked List
Export
Sort by
Relevance
1 of 15
1 Exploring generative AI literacy in higher education: student adoption, interaction, evaluation and ethical perceptions
Chen, K; Tallant, AC and Selig, I
Feb 6 2025 | INFORMATION AND LEARNING SCIENCES 126 (1/2) , pp.132-148
Enriched Cited References
PurposeCurrent knowledge and research on students' utilization and interaction with generative artificial intelligence (AI) tools in their academic work is limited. This study aims to investigate students' engagement with these tools.Design/methodology/approachThis research used survey-based research to investigate gener ... Show more
Full Text at Publisher
18 Citations
37 References
Related records
2 Why do graduate students use generative AI in thesis writing? the influence of self-efficacy, time pressure, and trust
Lin, CY and Wang, CC
Jun 2025 | CURRENT PSYCHOLOGY 44 (12) , pp.12071-12086
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Figure 2.7: Query Results from WoS

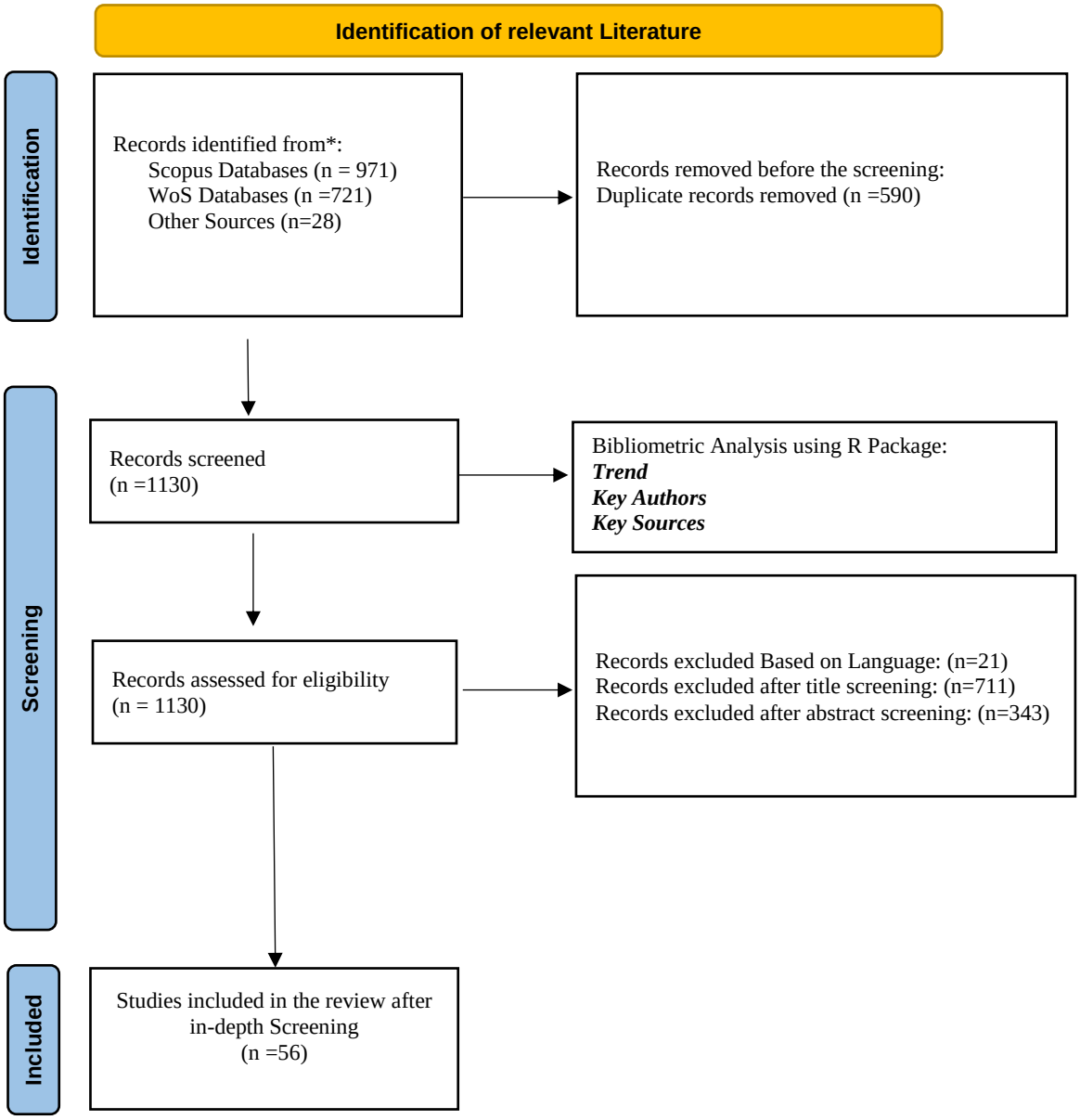

Figure 2.8: Flow diagram for the selection of study

Table 2.2: Summary Characteristics of Reviewed Studies on Generative AI Adoption (n = 56)

Category	Sub-category	Number of Studies	Remarks
Theories	TAM-based models	12	UTAUT-based models emerge as the most frequently employed theoretical framework, indicating their strong relevance in Generative AI adoption research
	UTAUT family	15	
	Value-Based Adoption Model (VAM)	2	
	Self-Determination Theory (SDT)	2	
	Other / hybrid models	25	
Stakeholder Focus	Students	41	The existing literature is predominantly student-centric, while empirical studies focusing on higher education teachers or faculty members remain critically limited.
	Teachers / Faculty members	5	
	Academic leaders / administrators	2	
	Mixed / Others	8	
Year of Publication	2019–2021	9	A substantial increase in publications is observed during the period 2024–2025, indicating that Generative AI adoption has emerged as a highly active and contemporary research area.
	2022–2023	13	
	2024–2025	34	
Country / Region	United States	10	Empirical evidence is largely concentrated in developed and technologically advanced countries. Although a small number of studies originate from India, these studies primarily focus on student populations, with no exclusive faculty-centred Generative AI adoption study identified to date.
	China	8	
	United Kingdom	6	
	South Korea	5	
	Malaysia	4	
	Saudi Arabia	4	
	Indonesia	3	
	India	3	
	Other countries	12	
	Multi-country / global studies	6	

The detailed list of studies included in the systematic literature review along with key attributes is presented in Annexure-1. Based on the systematic literature review and bibliometric analysis (Table 2.2), research on artificial intelligence and generative AI adoption has predominantly relied on established technology acceptance frameworks, with the Unified Theory of Acceptance and Use of Technology (UTAUT) emerging as the most widely applied model. This is to heighlit that the existing studies related to adoption of AI tools chatbots, ChatGPT etc. have examined student populations to a greater extent, while relatively fewer studies focus on university faculty members. Further, recent research highlights the increased use of construct such as trust and privacy in the adoption of advanced, data-intensive technologies such as generative AI.

3. Research Gap

Despite the significant increase in the research on artificial intelligence and generative AI adoption, several gaps remain evident. Firstly, although UTAUT has emerged as the dominant framework for explaining the technology adoption (Table 2.2), prior studies have mostly focused on students or users in developed countries, with limited empirical attention has been given to university faculty members in India. Second, while recent studies significantly utilize the construct such as trust and privacy as critical factors influencing adoption decisions in AI-driven systems, especially in the era of technology driven world, these constructs (trust and privacy) have not been conceptually integrated into models based on the UTAUT, examining generative AI adoption among faculty members. Therefore, systematic literature review clearly highlight that there is a lack of comprehensive, context-specific models that explain how traditional adoption factors, along with trust and privacy concerns, jointly influence behavioural intention and use behaviour towards generative AI among university faculty members in India. Since, the Indian higher education system is highly heterogeneous, comprising universities, affiliated colleges, and autonomous institutions with varying governance structures and technological infrastructures, therefore, to reduce institutional heterogeneity and ensure conceptual clarity, it is quite rational to consider faculty members working in universities in India.

To address these gaps, the present study proposes an extended UTAUT framework which integrates two more constructs such as trust and privacy, to examine generative AI adoption among university faculty members in India.

4. Research Problem

The rapid advancement of Generative AI tools has significantly transformed multiple sectors, including higher education, which plays a critical role in national development. Despite increasing exposure to Generative AI in academic activities, universities in India lack empirically validated insights into the determinants influencing faculty members' behavioural intention and actual use behaviour towards Generative AI. This gap is critical, as faculty members are central to teaching, research, and academic governance, and their adoption or resistance directly shapes how such technologies are integrated into institutional practices. The absence of systematic empirical

evidence poses challenges for universities seeking to align Generative AI adoption with academic integrity, pedagogical effectiveness, and policy expectations, particularly in the context of the rapid digital transformation envisioned under the National Education Policy (NEP) 2020 (Mhlanga, 2023; Peters & Green, 2024). In the absence of such empirical insights, universities face challenges in formulating informed strategies and policies for the effective and responsible integration of Generative AI into academic systems.

5. Conceptual Framework and Hypothesis Development

Based on the systematic literature review (Annexure-3 and Table 2.2) and bibliometric analysis conducted in the present study, the Unified Theory of Acceptance and Use of Technology (UTAUT) emerges as the most dominant and widely applied framework for examining technology adoption and use behaviour across organizational and educational contexts (Venkatesh et al., 2003; Venkatesh et al., 2012). Prior studies focusing on artificial intelligence and generative AI adoption in academic and professional environments consistently rely on UTAUT to explain behavioural intention and actual use, owing to its strong theoretical foundation and empirical robustness (Abbad, 2021; Vershitskaya et al., 2020; Rana et al., 2024). *Given its relevance for organizational users and decision-makers, UTAUT is adopted as the base model in the present study to examine generative AI adoption among university faculty members in India*.

According to the UTAUT framework proposed by Venkatesh et al. (2003), its consturcts such as performance expectancy, effort expectancy, and social influence directly influence the behavioural intention of the user while facilitating condition and behavioural intention significantly affects the actual use behaviour. Empirical evidence from various studies conducted on AI and educational technology adoption shows that these relationships remain significant in different academic settings, where faculty members evaluate and intend to use such technologies based on perceived usefulness, usability, social endorsement, and institutional support (Sharawy, 2023; Rana et al., 2024).

Further, from the systematic literature review, it was observed that the traditional UTAUT constructs may not fully capture the ethical and psychological concerns specially associated with generative AI systems. More specifically, trust has emerged as a critical and significant factor in the literature related to the AI adoption literature due to the self-directed, opaque, probabilistic behvaiour of AI technologies (Gefen et al., 2003; Lim et al., 2022). As per Mayer et al. (1995),

trust is defined as an individual's belief that a technological system is reliable, accurate, and operates in an ethical and predictable manner and being an educator of higher education, faculties are more concerned with the reliability of the output generated through these tools. In the prior studies, it has been found that trust significantly reduces the perceived uncertainty and risk, and therefore improving the behavioural intention of the end users (Patil et al., 2020; Lim et al., 2022). Further, in academic contexts, faculty members are more intend to adopt GenAI tools, when they trust that the content generate by the GenAI systems is reliable and it also align with academic integrity and professional standards (Dwivedi et al., 2023; Rana et al., 2024). Moreover, patil et al. (2020) in his study on GenAI adoption has observed that trust also contributes to sustained use behaviour as their confidence is built during the continuous interaction with AI systems (Patil et al., 2020). In consideration of the above findings and facts, trust is proposed to be incorporated into the classical UTAUT framework as a determinant of both behavioural intention and use behaviour.

Privacy represents another emerging construct that has been found important construct in recent generative AI adoption related studies, particularly reflecting users' concerns regarding the protection and handling of personal and institutional data which they upload during the use of the AI systems. As per Malhotra et al. (2004), privacy refers to individuals' concerns regarding the collection, storage, and potential misuse of personal or institutional data by these AI systems. The Internet Users' Information Privacy Concerns framework conceptualizes the privacy construct via different dimensions such as data collection, control over storage of the uploaded content, and awareness, which influence users' perceptions of security and ethics towards data handling (Malhotra et al., 2004). It has been indicated in the existing research that privacy concerns are especially salient in higher education contexts, where faculty members handle sensitive research data, intellectual property, and important information related to the students (Belanger & Crossler, 2011; Culnan & Armstrong, 1999). Various empirical GenAI related studies further suggest that users may develop behavioural intention and use behaviour to adopt AI technologies if they feel confident in privacy safeguards and data governance mechanisms (Rana et al., 2024; Patil et al., 2020). In addition, the user's concerns regarding data security, confidentiality of academic content, and potential misuse of various information related to the their organisations may influence faculty members' willingness and intention to adopt generative AI tools. Therefore, the present study also proposed to incorporate privacy construct into the UTAUT framework as a determinant of both

behavioural intention and use behaviour towards generative AI.

In liue of the above, the present study proposes an extended conceptual framework integrating trust and privacy along with the core UTAUT constructs to explain behavioural intention and use behaviour towards generative AI among university faculty members in India. Based on this framework, the following hypotheses are proposed:

H1: *"Performance expectancy positively influences behavioural intention to adopt generative AI among university faculty members in India".*

H2: *"Effort expectancy positively influences behavioural intention to adopt generative AI among university faculty members in India".*

H3: *"Social influence positively influences behavioural intention to adopt generative AI among university faculty members in India".*

H4a: *"Trust positively influences behavioural intention to adopt generative AI among university faculty members in India".*

H4b: *"Trust positively influences use behaviour towards generative AI among university faculty members in India".*

H5: *"Facilitating conditions positively influence use behaviour towards generative AI among university faculty members in India".*

H6a: *"Privacy significantly influences behavioural intention to adopt generative AI among university faculty members in India".*

H6b: *"Privacy significantly influences use behaviour towards generative AI among university faculty members in India".*

H7: *"Behavioural intention positively influences use behaviour towards generative AI among university faculty members in India".*

The proposed relationships among the constructs are illustrated in Figure 2.9. In order to empirically test these relationships, each construct in the model is operationalized using measurement items adapted from established and validated scales in prior literature. The constructs are defined both in their theoretical sense and in the specific context of generative AI adoption among university faculty members in India. The following sub-section presents the definitions of the constructs and their contextual interpretation for the present study.

5.1. Operationalization of Constructs in the Context of Generative AI Adoption

Performance expectancy refers to the extent to which higher education faculty members believe that using Generative AI can enhance their teaching effectiveness, research productivity, academic content development, and decision-making (Venkatesh et al., 2003; Dwivedi et al., 2023)

Effort expectancy is defined as the degree of ease associated with the use of GenAI for academic purposes without excessive technical or cognitive effort. (Venkatesh et al., 2003, Rana et al. 2024).

Social influence refers to the degree to which faculty members perceive that colleagues, departmental leadership, institutional policies, and professional networks encourage or expect them to use GenAI for academic purposes (Venkatesh et al., 2003, Rana et al. 2024).

Facilitating conditions refer to the degree to which an individual believes that an organizational and technical infrastructure exists to effectively use GenAI for academic purposes (Venkatesh et al., 2003, Dwivedi et al., 2023, Rana et al. 2024).

Trust refers to faculty members' confidence in the reliability, accuracy, transparency, and ethical use of Generative AI for academic purpose. (Gefen et al., 2003; Lim et al., 2022).

Privacy refers to faculty members' concerns about the security, confidentiality, and appropriate use of academic, institutional, and personal data when using GenAI for academic purposes (Malhotra et al., 2004; Belanger & Crossler, 2011).

Behavioural intention refers to faculty members' intention and willingness to adopt Generative AI for academic purposes (Venkatesh et al., 2003; Venkatesh et al., 2012, Dwivedi et al., 2023).

Use behaviour refers to the extent of actual use of GenAI by faculty members for academic purposes (Venkatesh et al., 2003, Dwivedi et al., 2023).

6. Research Questions

RQ1: What factors influence the behavioural intention to adopt generative AI among university faculty members in India?

RQ2: What factors influence the use behaviour of generative AI among university faculty members in India?

RQ3: To what extent does behavioural intention influence the actual use behaviour of generative AI among university faculty members in India?

7. Research Objectives

Based on the gap identified from the literature review, the research work proposed to cover the following objectives:

1. To assess the influence of performance expectancy, effort expectancy, and social influence on behavioural intention to adopt generative AI among university faculty members in India.
2. To investigate the influence of trust and privacy on behavioural intention and use behaviour towards generative AI among university faculty members in India.
3. To examine the influence of facilitating conditions on use behaviour towards generative AI among university faculty members in India.
4. To assess the influence of behavioural intention on use behaviour towards generative AI among university faculty members in India.

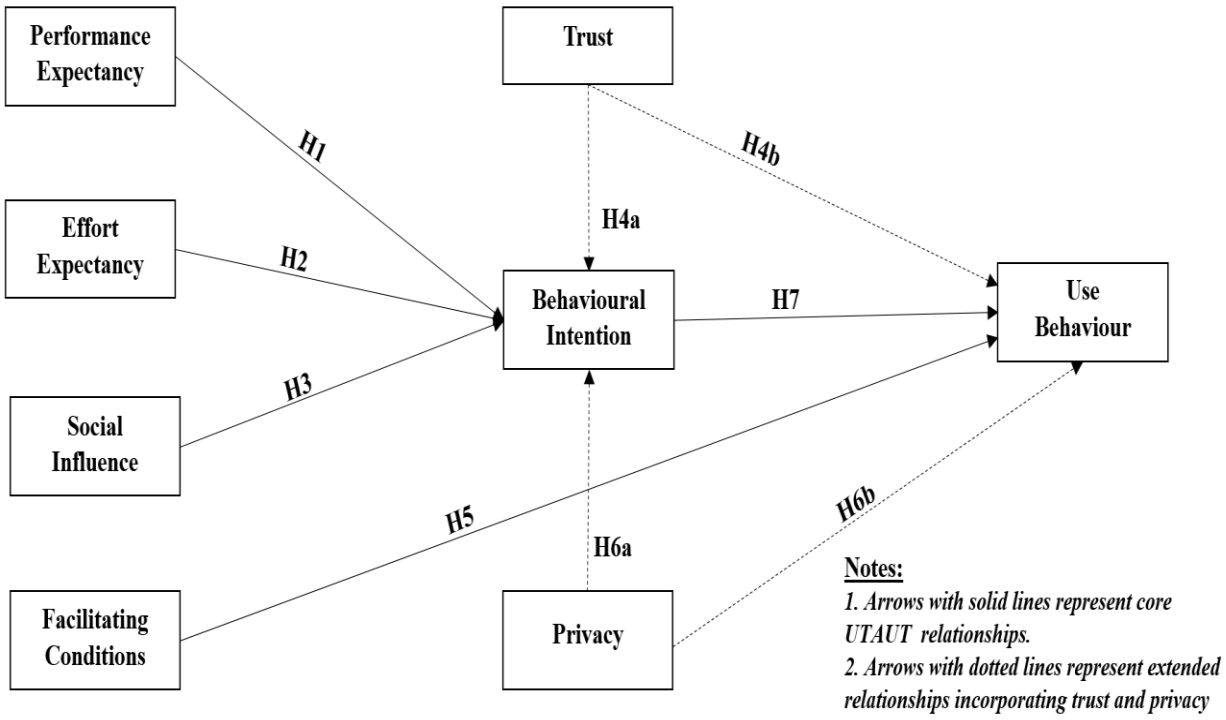

Figure 2.9: Proposed Model

8. Research Methodology

The study proposes to adopt a quantitative, explanatory research design to examine the determinants of generative AI adoption among university faculty members in India. The study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), extended by integrating Trust and Privacy as additional constructs. Data will be collected through a structured questionnaire which will be developed using validated measurement scales adapted from prior studies with items measured on a Likert scale.

The target population of the study comprises full-time faculty members employed in universities across India. To ensure a well-defined, homogeneous, and representative sampling frame, the population is restricted to university-level faculty, deliberately excluding faculty from affiliated colleges and standalone institutions. This boundary is methodologically justified on the grounds that university faculty operate within comparable institutional structures, digital infrastructure conditions, and research-oriented professional roles, thereby minimizing extraneous heterogeneity in adoption behaviour (Popenici & Kerr, 2017). The sampling frame will be constructed using data from the All India Survey on Higher Education (AISHE), published annually by the Ministry of Education, Government of India, and supplemented by institutional data available from the University Grants Commission (UGC) website. AISHE provides a comprehensive, government-verified census of all higher education institutions in India including university-wise faculty counts across disciplines and institutional types (AISHE, 2022). This approach ensures that the sampling frame is systematic, transparent, and replicable. The study will include universities across all categories recognised by UGC, namely central universities, state universities, deemed universities, and universities established under state private Acts, covering diverse disciplines and geographic regions of India. A mixture of convenience & purposive sampling technique will be employed to ensure proportional representation across institutional categories and geographic zones (North, South, East, West, and Central India). The sample size will be determined using multiple approaches: the Krejcie and Morgan (1970) table, G*Power software (power = 0.80, effect size = 0.15, significance level = 0.05), and the ten-times rule (Hair et al., 2017; Faul et al., 2007). Based on these approaches, a target sample of approximately 350–400 respondents is anticipated.

The collected data will be analyzed using Structural Equation Modelling (SEM) to test the proposed research hypotheses and examine the relationships among the constructs. The specific SEM approach (CB-SEM or PLS- SEM) will be determined after examining the nature of the data and assessing key statistical assumptions such as normality and sample characteristics. Reliability and validity of the measurement model will be assessed prior to evaluating the structural model. The results will provide empirical evidence on the determinants influencing behavioural intention and use behaviour towards generative AI.

9. Significance of the Study

The study makes several important contributions to theory and practice. From a theoretical perspective, it extends the UTAUT framework by integrating Trust and Privacy, thereby enhancing its applicability to emerging and data-intensive technologies such as Generative AI. Specifically, by incorporating Privacy as a determinant of both behavioural intention and use behaviour, the study addresses a theoretically underexplored path in extant UTAUT-based research and contributes to more comprehensive modelling of GenAI adoption dynamics. The study is among the first to develop and empirically validate a faculty-centered Generative AI adoption model in the Indian higher education context — an area identified as critically under-researched in the systematic review. The study also contributes to the relatively limited body of literature examining technology adoption among university faculty members, particularly within the Indian context, which remains under-explored.

From a managerial and practical perspective, the findings will offer valuable insights for university administrators, policymakers, and technology providers to understand the key factors influencing faculty adoption of Generative AI. These insights can support informed decision-making related to digital transformation strategies, capacity building, and responsible AI implementation in higher education institutions. The study's insights on privacy and trust can further support institutions in designing responsible AI governance frameworks and faculty development programs.

10. Limitations and Future Scope of the Study

Despite its contributions, the study has certain limitations. First, the use of cross-sectional data may restrict the ability to capture changes in adoption behaviour over time. Second, the reliance on self-reported responses may introduce common method bias. Third, the study does not explicitly examine the moderating effects of demographic or institutional variables, which may influence adoption behaviour. Additionally, the findings may have limited generalizability beyond the Indian higher education context. Future research may build upon the findings of this study by adopting a longitudinal research design to examine changes in Generative AI adoption over time. Further studies may incorporate moderating variables such as gender, institutional type, teaching experience, or AI literacy to explore heterogeneity effects. Comparative studies across countries or educational systems could enhance the generalizability of the results. Additionally, future research may extend the proposed model by integrating constructs related to ethical concerns, transparency, or regulatory awareness in the context of Generative AI adoption.

Annexure-1

Proposed Semester-wise plan of work and targets to be achieved:

S. No.	Semester	Activities	Period
1	I	Course Work	Mar-Aug, 25
2	II	Preparation and Defence of the Thesis Proposal (Synopsis)	Aug, 25 – Feb, 26
3	III	Questionnaire Development & Validation, Sampling Design, Pilot Testing and Refinement of Questionnaire	Mar-Aug, 26
4	IV	Data Collection, Data Preparation: Coding and Cleaning	Aug, 26 – Feb, 27
5	V	Data Analysis and Results	Mar-Aug, 27
6	VI	Thesis Writing, and Pre-PhD Seminar	Aug, 27 – Feb, 28

Annexure-2:

Summary of Constructs and Items to be Adapted from the Literature

Construct	Adapted From	No. of Items
Performance Expectancy	Venkatesh et al. (2003)	4
Effort Expectancy	Venkatesh et al. (2003)	4
Social Influence	Venkatesh et al. (2003)	4
Facilitating Conditions	Venkatesh et al. (2003)	4
Trust	Gefen et al. (2003); Lim et al. (2022)	4
Privacy	Malhotra et al. (2004)	4
Behavioural Intention	Venkatesh et al. (2003)	3
Use Behaviour	Venkatesh et al. (2003)	3

Annexure-3

Detailed Summary of Studies included in Systematic Literature Review:-

S. No.	Title	Authors	Year	Study Participants	Statistical Analysis	Research Approaches	Sample size	Researched Technologies	Research Location	Models/ Theories Used	Factor as IV	Factor as DV	Variable as Moderator
1	"Investigating university students' intention to use mobile learning management systems in Sweden"	Asher Irfan Saroia and Shang Gao	2019	Students	SEM (PLS)	Quantitative	130	mLMS	Sweden	Extended TAM	PMV(Perceived Mobility Value), AR(Academic Relevance), UMS(University Management Support) are the independent variables	Perceived Usefulness, perceived ease of use and attitude are the dependent variables	Perceived Mobility Value (PMV), Academic Relevance (AR) and University Management Support(UMS) are the moderating variables
2	"Adoption of AI-Chatbots to Enhance Student Learning Experience in Higher Education in India"	Sandu, N., & Gide, E.	2019	Students	Descriptive statistics	Quantitative	47	Chatbots	India	Factors identified no model used.	'Technological ease', 'student engagement', and 'communication efficiency' are the independent variables.	Learning experience' is the dependent variable.	Institutional support' and 'technological infrastructure' may implicitly behave like moderating variable.
3	"Work-in-Progress: A Preliminary Study on Students' Acceptance of Chatbots for Studio-Based Learning"	Kumar, & Silva, P. A	2020	Students	Descriptive statistics	Mixed	30	Chatbots	Malaysia	Extended TAM	Compatibility, human likeness, perceived ease of use, perceived usefulness, Attitude, Internet privacy are independent variables.	Behaviour Intent and usage are dependent variables.	Internet privacy is a moderating variable.
4	"A Chatbot for Learning Chinese: Learning Achievement and	Chen, H. L., Vicki Widarso, G., & Sutrisno, H.	2020	Students	ANOVA, PLS	Quantitative	58	chatbots	Taiwan	TAM	Perceived ease of use, perceived usefulness and perceived enjoyment are	Behavior intention and learning achievement are depndent variables.	Not specified

	Technology Acceptance"										independent variable.		
5	"Understanding Student Acceptance and Use of Chatbots in the United Kingdom Universities: A Structural Equation Modelling Approach"	Almahri, F. A. J., Bell, D., & Merhi, M	2020	Students (UG/PG-Computer Science)	SEM	Quantitative	431	Chatbots	London	UTAUT2	'performance expectancy', 'effort expectancy', 'social influence', 'facilitating conditions', 'hedonic motivation', and 'habit' are included in the study as independent variables.	Behavior Intention and Usage behavior are the dependent variables.	Age, Gender and Experience are moderating variables
6	"A comparison of faculty and student acceptance behavior toward learning management systems"	Kim, Yoon & Kim	2021	Mixed (Students and lecturers)	SEM (PLS)	Quantitative	376	Chatbot integrated LMS	South Korea	Extended TAM (TAM , self-efficacy, subjective norm, enjoyment factor , and computer anxiety are the independent variable.	Individuals' Self-efficacy, subjective norm, enjoyment, and computer anxiety)	Behavior intention is the dependent variable.	Age, Gender, experience
49	"Design and Acceptance of Chatbots for Information Automation in University Classrooms"	F. Rejón-Guardia & G.A. Vich-I-Martorell	2020	Students	SEM	Quantitative	-	chatbots	Spain	UTAUT2	design', 'user-interface', 'multimedia integration' are the independent variables	Intention of use is the dependent variable	-
7	"Adoption of Chatbots for Learning among University Students: Role of Perceived Convenience and Enhanced Performance"	Malik, R., Shrama, A., Trivedi, S., & Mishra, R.	2021	Students	SEM	Quantitative	372	Chatbots	India	Extended TAM	'Perceived usefulness', 'perceived ease of use', 'perceived convenience', and 'attitude' are the independent variables in the study.	The dependent variable in the study are 'intention to adopt' chatbots and 'enhanced performance'	Attitude' is the moderating variable on all other variables impacting 'intention to adopt'

8	"The Evaluation of Chatbot as a Tool for Health Literacy Education among Undergraduate Students"	Mokmin, N. A. M., & Ibrahim, N. A.	2021	Students	Descriptive statistics	Qualitative and quantitative	75	chatbots	Malaysia	UTAUT2	Chatbot features and user engagement were the independent variables.	Health literarcy improvement is the dependent variables	Perception and technology acceptance are the moderating factors
9	"Understanding the impact of knowledge management factors on the sustainable use of AI-based chatbots for educational purposes using a hybrid SEM-ANN approach"	Mohammed A. Al-Sharafi, Mostafa Al-Emran, Mohammad Iranmanesh, Noor Al-Qaysi, Noorminshah A. Iahad & Ibrahim Arpaci	2022	Students	Hybrid SEM-ANN approach	Quantitative	448	Chatbot	Malaysia	expectation confirmation model (ECM) (expectation confirmation,perceived usefulness, and satisfaction), combined with the knowledgemanagement (KM) factors (knowledge sharing(KS), knowledge acquisition(KAc),and knowledge application(KA)) to understand sustainable use of chatbots	EC, KS, Kac, KA	PU, Satisfaction, Sustainability	NIL
10	"AI-based chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-neural network modelling approach"	Mohd Rahim, N.I.; A. Iahad,N.; Yusof, A.F.; A. Al-Sharafi, M.	2022	Students	SEM-ANN	Quantitative	300	Chatbot	Malaysia	UTAUT2 Combined with(chatbot adoption success factor framework in the private service sector (design, ethics, and interactivity))	Interactivity, Design, Ethics, Performance Expectancy, Habit, Facilitating Conditions, Hedonic Motivation and Social Influence are Independent variables.	Perceived Trust, Behavioral Intention and Use of Chatbots are dependent variables	'User Experience', 'Institutional Support', 'Technological Familiarity' and 'Social Influence' can be inferred to play a potential moderating variable role as per the context of the paper. However, the paper doesn't mention any moderating variables.

11	"Investigating the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt"	Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A.	2022	Students	SEM	Quantitative	385	Chatbot	Egypt	UTAUT	Performance expectancy, effort expectancy and Social Influence	Behaviour Intention	Age, Gender
12	"Examining students' intention to use ChatGPT: Does trust matter?"	Rahman, M. S., Sabbir, M. M., Zhang, J., Moral, I. H., & Hossain, G. M. S	2022	Students	SEM	Quantitative	344	ChatGPT	Bangladesh	TAM	The hypothesized Independent Variables are Perceived usefulness of ChatGPT, perceived ease of use of ChatGPT, perceived enjoyment by using ChatGPT, and perceived informativeness of chatGPT.	The Dependent Variables are individuals' Attitude towards ChatGPT and the their intention to use ChatGPT.	The hypothesized Moderating Variable is individuals' Trust on ChatGPT which prompted the connection between perceived enjoyment of using ChatGPT and their attitude towards ChatGPT use.
13	"Investigating the Acceptance of Applying Chat-Bot (Artificial Intelligence) Technology among Higher Education Students in Egypt"	Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A.	2022	Students	Sem, descriptive, correlations , regressions	Quantitative	385	chatbots	Egypt	UTAUT, Experience and voluntariness removed as Moderator. Facilitating condition and behavior use also removed as construct from the original mode.	Performance expectatncy', 'effort expectancy' and 'social influence' are the independent variables	behavior intention to accept' chatbots is the dependent variable.	Age' and 'Gender' are moderating variables.
14	"Using Chatbots as AI Conversational Partners in Language Learning"	Belda-Medina, J., & Calvo-Ferrer, J. R. (	2022	Teachers	SEM(PLS)	Qualititave and quantitative	176 (115 spain+ 61 poland)	chatbots	Spain and Poland	Extended TAM	'Perceived ease of use ', ' perceived usefulness' , 'attitudes ' , and 'self-efficacy' are the independent variables in the study.	'Behavioral intention to use' is the dependent variable.	'gender' and 'educational setting' are identified as moderating variables.

15	"To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology"	Artur Strzelecki	2023	Students	SEM (PLS)	Quantitative	534	ChatGPT	Poland	UTAUT2	Habit, Performance Expectancy, Hedonic Motivation, Personal Innovativeness, Effort Expectancy, Social Influence, Facilitating Conditions are the independent variables.	Behavioral Intention and Use Behavior are the dependent variables.	Gender and Study Year
16	"Investigating student acceptance of an academic advising chatbot in higher education institutions"	Ghazala Bilquise, Samar Ibrahim, Sa'Ed M.Salhieh	2023	Students	SEM (PLS)	Quantitative	207	Chatbot	UAE	UTAUT+ Self Determination Theory(SDT)+ the service Robot Acceptance(sRAM) model	'Perceived Ease of Use' (PEU), 'Perceived usefulness'(PU), 'Social influence'(SI), 'Perceived Autonomy'(PA), 'Anthropomorphism' (AN) and 'Perceived Trust' (PT) are hypothesized as independent variables.	Behavioral Intention is hypothesized as dependent variable.	
17	"To use or not to use? Understanding doctoral students' acceptance of ChatGPT in writing through technology acceptance model"	Zou and Huang	2023	Students (Ph.D)	SEM	Quantitative	242	ChatGPT	China	TAM	'Perceived usefulness' , 'Perceived ease of use', 'Perceived enjoyment' , 'Perceived informativeness' and 'Trust' are the hypothesized independent variables.	Attitude' and 'Behavior Intention' are the dependent variables.	Experience
18	"Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation	Cong Doanh Duong, Trong Nghia Vu, Thi Viet Nga Ngo	2023	Students	SEM	Quantitative	1389	ChatGPT	Vietnam	Modified TAM	Effort expectancy' and 'performance expectany' are independent variables.	Behavioral Intention' & 'Use-behavior' are dependent variables.	Knowledge sharing(KS)

	model with knowledge sharing as a moderator"												
19	"Modeling Students' Perceptions of Chatbots in Learning: Integrating Technology Acceptance with the Value-Based Adoption Model"	Ahlam MohammedAl-Abdullatif	2023	Students	SEM (PLS)	Quantitative	432	Chatbots	Saudi Arabia	TAM+VBM(Value based model)	Perceived ease of use, Perceived Usefulness, Perceived Enjoyment and Perceived risk are the independent variables	Attitude, Perceived Value and Acceptance are the dependent variables	Perceived Risk as moderating variable, but identified as insignificant influence
20	"Acceptance of AI in Semi-Structured Decision-Making Situations Applying the Four-Sides Model of Communication—An Empirical Analysis Focused on Higher Education"	Greiner, C., Peisl, T. C., Höpfl, F., & Beese, O.	2023	Diverse experience in grading	MAXQDA	Qualitative	10	AI	Germany	TAM combined with four sides communication model	transparency, trust, perceived usefulness, perceived ease of use, and ethical considerations are the independent variables	Acceptance of AI' is the dependent variable	Human oversight, familiarity with AI and scenario specific factors are moderating variables
21	"Modeling Students' Perceptions of Chatbots in Learning: Integrating Technology Acceptance with the Value-Based Adoption Model"	Al-Abdullatif, A. M.	2023	students	SEM (PLS)	Quantitative	432	chatbots	Saudi Arabia	TAM and VAM	Perceived ease of use', 'perceived usefulness', 'perceived enjoyment' and 'perceived risks' are independent variables.	Attitude' and 'acceptance' are dependent variables	perceived value' is the moderating variable.

22	"ChatGPT awareness, acceptance, and adoption in higher education: the role of trust as a cornerstone"	Muhammad Farrukh Shahzad; Shuo Xu; Iqra Javed	2024	University students	PLS-SEM (SmartPLS 4)	Quantitative survey	320	ChatGPT (Generative AI chatbot)	Beijing, China (six universities)	TAM (extended with PI) + Trust as moderator	ChatGPT awareness (CGPTAW); Perceived ease of use (PE); Perceived usefulness (PU); Perceived intelligence (PI)	ChatGPT adoption intention (CGPTAI)	Perceived trust (PT)
23	"Exploring intention of undergraduate students to embrace chatbots: from the vantage point of Lesotho"	Ayanwale, Musa Adekunle, and Rethabile Rosemary Molefi	2024	Students(UG)	SEM covariance based	Quantitative	842	Chatbot	Lesotho	Theory of diffusion of innovation	'Relative Advantages', 'Compatibility', 'Trialability' , 'Perceived Trust', 'Perceived Usefulness' and 'Perceived Ease of Use' were hypothesized as independent variable in the study.	'Behavioral Intention' was hypothesized as a dependent variable in the study.	-
24	"ChatGPT adoption and anxiety: a cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT)"	Tribikram Budhathoki, Arar irar,Eric Tchouamou Njoya and Achyut Timsina	2024	Students	SEM	Quantitative	239	ChatGPT	United Kingdom	UTAUT + Anx(Anxiety)	Performance Expectancy, Effort Expectancy, Social Influence , Facilitating Conditions , Anxiety are hypothesized as independent variables	Behavioral Intention is hypothesized as dependent variable.	Anxiety is the primary moderating variable in the study.
25	"Understanding the diffusion of AI-generative (ChatGPT) in higher education: Does students' integrity matter?"	Mohammed Bouteraa , Saeed Awadh Bin-Nahwan, Meshari Al-Daihani, et.al	2024	Students (Non-Science)	SEM(PLS)	Quantitative	921	ChatGPT	ASEAN	UTAUT + Social cognitive theory(SCT)	'Performance Expectancy', ' Effort Expectancy', 'Social Influence', 'Educational Self-Efficacy', 'Technology Self-Efficacy', 'Personal Anxiety' and 'Student Integrity' are hypothesized as independent variables.	Use behavior' is the dependent variable.	INT(Students' integrity) is the moderating variable.

26	"Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study"	Hayder Albayati	2024	students	SEM(PLS)	Quantitative	603	ChatGPT	ONLINE	TAM+P+T+SI+SE	PEU,PU, SE(Security),P(privacy),SI(Social Influence), Trust(T)	'Behavioral Intention', 'Attitude', 'Perceived Usefulness', 'Perceived Ease of Use', 'Trust' and 'Social Influence' are dependent variables	
27	"Investigating factors of students' behavioral intentions to adopt chatbot technologies in higher education: Perspective from expanded diffusion theory of innovation"	Musa Adekunle Ayanwale and Mdutshekelwa Ndlovu	2024	Students	Hybrid SEM-ANN approach	Quantitative	842	Chatbot	Malaysia	Theory of Diffusion of Innovation+ TAM	'Relative advantages', 'Compatibility', 'Trialability', 'Trust', 'Perceived usefulness' and 'Perceived ease of use' are hypothesized as independent variables.	'Behavioral intention to use' chatbots for purpose of academics is hypothesized as dependent variable.	
28	"ChatGPT in higher education: factors influencing ChatGPT user satisfaction and continued use intention"	Chengcheng Yu, Jinzhe Yan and Na Cai	2024	Students	SEM	Quantitative	328	ChatGPT	United States	TAM	Compatibility' and 'Efficiency' are independent variables.	Satisfaction', and 'Continued Use intention' are dependent variables.	Perceived ease of use' and 'perceived usefulness' are moderating variables.
29	"Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour"	Stanislav Ivanov, Mohammad Soliman, Aarni Tuomi, Nasser Alhamar Alkathiri, Alamir N. Al-Alawi,	2024	Mixed (Students and lecturers)	SEM(PLS)	Quantitative	130 lecturers and 168 students= 298	GenAI	International	Theory of planned behaviour	Perceived strengths', 'weaknesses', 'benefits', and 'risks' associated with Gen AI are the independent variables.	Intention to use' Gen AI is the dependent variable.	Attitude', 'subjective norms' and 'perceived behavioural control' are the moderating variables.

30	"Understanding students' adoption of the ChatGPT chatbot in higher education: the role of anthropomorphism, trust, design novelty and institutional policy"	Athanasios Polyportisa, and Nikolaos Pahos	2024	Students	SEM (Using STATA 14 software)	Quantitative	355	ChatGPT	Netherlands	meta UTAUT	Performance Expectancy, Effort Expectancy, Social Influence ,Facilitating Conditions, Anthropomorphism, Design Novelty, Trust, Institutional policy are the independent variables.	Use behavior is the dependent variable	Institutional policy is negatively moderating the effect of behavior intention on use behavior
31	"Examining Students' Acceptance and Use of ChatGPT in Saudi Arabian Higher Education"	AbuElnasr E. Sobaih , Ibrahim A. Elshaer and Ahmed M.Hasanein	2024	Students(Management)	SEM (PLS)	Quantitative	520	ChatGPT	Saudi Arabia	UTAUT2	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition are the independent variables.	Behavioral Intention & Use Behavior are the dependent variables.	No Explicit moderating variables identified
32	"Revolutionizing education: Artificial intelligence empowered learning in higher education"	Rahiman & Kodikal,	2024	Teachers	SEM	Quantitative	250	AI chatbots	Asia District, Peru	UTAUT	Awareness ,Perceived risks ,Performance Expectancy, Effort Expectancy	Facilitating Condition, Adoption, Work Engagement,AI in highert Education	Attitude and behaviour as moderating variables
33	"Economics students' behavioural intention and usage of ChatGPT in higher education: a hybrid structural equation modelling-artificial neural network approach"	iddrisu Salifua,b , Francis arthurc Richard Solomon osei-Yawe	2024	Students (Economics)	SEM-ANN	Quantitative	306	ChatGPT	Ghana	UTAUT2	'perceived trust', 'hedonic motivation' , 'facilitating conditions', 'design' , 'social influence', and 'interactivity' are the independent variables.	Behavior Intention' and 'Actual use of ChatGPT' are the dependent variables.	Not expressely mentioned, but in future study age, gender and experience may be considered as moderating variables.

34	"AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models."	Salifu, I., Arthur, F., Arkorful, V., Abam Nortey, S., & Solomon Osei-Yaw, R	2024	Students	SEM (PLS)	Quantitative	373	Chatbot	China	UTAUT and ECM	PE,EE,SI, FC, CF(Confirmation), SA(Satisfaction), PI(Personal Innovativeness)	BI and UB	Age, Gender
35	"Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: effect of intent to use, verification of information and responsible use"	Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Huamaní Jordan, O., López Roca, C., & Saavedra Tirado, K.	2024	Students	SEM (PLS)	Quantitative	499	ChatGPT	Peru	UTAUT2, attitudional component of Mitcham's philosophical framework, PATT-SQ-SE model	Cognitive component (Importance, Easy to use(EUS), Perceived opportunity(POP), Perceived Risk(PRI)), Affective component(Interest(INTU), Positive emotions, Boredom(BORE), Negative emotions(NEGEMOS), Perceived usefulness(PUS))	Behavioural component(Acceptance(ACC).Frequently used Intention, Intention to Verify information(INTU), Responsible use of chatGPT)	Acceptance
36	"Acceptance and use of ChatGPT in the academic community"	Strzelecki, A., Cicha, K., Rizun, M., & Rutecka, P.	2024	Students and Teachers	SEM(PLS)	Quantitative	629	ChatGPT	Poland	UTAUT2+PI	The identified independent variables are "Performance Expectancy," "Effort Expectancy," "Social Influence," "Facilitating Conditions," "Hedonic Motivation," "Price Value," and "Habit." Moreover, "Personal Innovativeness" was added as an independent variable impacting	The dependent variable identified are "Behavioral Intention" and "Use behavior". However, behavior intention directly influences Use behavior.	Gender, Age

											behavioral intention.		
37	"Understanding Teachers' Perspective toward ChatGPT Acceptance in English Language Teaching"	Mutammimah , H., Rejeki, S., Kustini, S., & Amelia, R.	2024	Teachers	SEM	Quantitative	114	ChatGPT	Indonesia	TAM	The variables considered independent in this paper are "Perceived Usefulness" of ChatGPT in and "Perceived Ease of Use" of chatGPT.	The variables considered as dependent variables are "Attitude Toward Using" ChatGPT, "Behavioral Intention to Use" chatGPT and "Actual System Use".	A factor identified as moderator is "attitudes" of teachers, which persuaded the connection between "perceived usefulness" , "perceived ease of use", and their "behavioral intention".
38	"A longitudinal study on artificial intelligence adoption: understanding the drivers of ChatGPT usage behavior change in higher education"	Polyportis, A.	2024	Students	SEM	Quantitative	222	ChatGPT	Netherlands	UTAUT + temporal dynamics	Trust Change(TC), Emotional Creepiness change(ECC),Perceived Behavioural control change(PBCC) are the independent variables	Usage Behaviour change (UBC) is the dependent variable.	Gender, Age
39	"ChatGPT as a CALL tool in language education: A study of hedonic motivation adoption models in English	Qu, K., & Wu, X	2024	Students	SEM	Quantitative	189	ChatGPT	United Kingdom	hedonic motivation system adoption model (HMSAM)	The hypothesized independent variables are "Perceived Ease of Use", "Perceived Usefulness" , and "Personal Innovativeness in Information Technology".	Behavioral intention is hypothesized as dependent variable.	While hypothesized moderating variables are Boredom, Curiosity , Control , and Joy .

	learning environments"												
40	"From concerns to benefits: a comprehensive study of ChatGPT usage in education"	Jo, H.	2024	Students	SEM (PLS)	Quantitative	273	ChatGPT	South Korea	Self-determination theory, diffusion of innovation, TAM, privacy theory and technostress, affect theory, and theory of planned behavior	The identified Independent Variables are Self-learning capabilities of AI, personalization, novelty value, and perceived individual impacts	The hypothesized Dependent Variables are Behavioral intention to use ChatGPT and actual behavior regarding the use of ChatGPT.	The identified moderating variables are individual's privacy concerns, technophobia with respect to the individual technology, and their individual guilt feeling were examined as variables that could adversely impact the hypothesized dependent variables in the study.
41	"Exploring Factors Shaping Chinese English Learners' Engagement with Large Language Models for Vocabulary Learning"	Wang, X., & Reynolds, B. L.	2024	Students	SEM	Quantitative	568	ChatGPT	China	SDT(Self-determination theory)+ UTAUT	The identified Independent Variables are individuals' Perceived autonomy, individuals' perceived competence, individuals' perceived relatedness with chatgpt, individuals' performance expectancy, individuals' effort expectancy, and social influence on individual.	The Dependent Variable is individuals' Behavioral intention to utilize large language models in context of vocabulary learning.	The researchers considered Facilitating conditions as moderating variable but it failed to significantly influence usage intention of LLM.

42	"Factors Affecting the Adoption and Use of ChatGPT in Higher Education"	Alshammari, S. H., & Alshammari, M. H.	2024	Students		Quaantitative	136	ChatGPT	Saudi Arabia	UTAUT	Individuals' Performance Expectancy , Individuals' Effort Expectancy, Social Influence on individuals, Facilitating Condition are the independent variables	Individuals' behavior intention to use ChatGPt is the dependent variable.	None tested
43	"Investigating student acceptance of an academic advising chatbot in higher education institutions."	Bilquise, G., Ibrahim, S., & Salhieh, S. E. M.	2024	Students	SEM(PLS)	Quantitative	207	chatbots	United Arab Emirates	TAM, UTAUT, self-service technologies models, the Service Robot Acceptance (sRAM) model, Self Determination Theory (SDT) model	'Perceived Ease of Use' , 'Perceived Usefulness' , 'Social Influence' , 'Perceived Trust' , 'Perceived Autonomy' , and 'Anthropomorphism' are the independent variables.	'Behavioral Intention to adopt' the advising chatbot is the dependent variable.	
44	"The Merlin Project: Malaysian Students' Acceptance of an AI Chatbot in Their Learning Process"	Mai, N. E. O.	2024	Students	SEM(PLS)	Quantitative	413	chatbots	Malaysia	TAM	'Perceived ease of use' , 'perceived usefulness', 'time-saving feature' , 'academic self-efficacy' and 'electronic word-of-mouth' are the independent variables.	Intention to adopt' and 'actual use' are the dependent variables	Awareness' of benefits may implicitly be termed as moderating variables.
45	"AI Chatbot Adoption in Academia: Task Fit, Usefulness and Collegial Ties"	Soodan, V., Rana, A., Jain, A., & Sharma, D	2024	Teachers	SEM(Covariance based), CFA	Qualititave and quantitative	448	Chatbots	India	Extended TAM	The studied independent variables identified are 'task characteristics', 'technology characteristics', and 'social network factors' such as 'density' , 'homophily' and connectedness'.	The dependent variables included in the study 'intention to use' chatbots	the moderating variables are 'task-technology fit' and 'perceived usefulness' .

46	"Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education"	Pillai, R., Sivathanu, B., Metri, B., & Kaushik, N.	2024	Students	SEM (PLS)	Quantitative	1380	Chatbots	India	Extended TAM	Perceived Ease of Use ', 'Perceived Usefulness' , 'Personalization ', ' Interactivity ', 'Perceived Trust ', 'Anthropomorphism ', and 'Perceived Intelligence ' are the independent variables.	Adoption Intention' and 'Actual usage' are the dependent variables.	The 'stickiness to learning from human teachers' is the moderating variables.
47	"Adoption of ChatGPT by university students for academic purposes: Partial least square, artificial neural network, deep neural network and classification algorithms approach"	Mahmud, A., Sarower, A. H., Sohel, A., Assaduzzaman, M., & Bhuiyan,	2024	Students	partial least squares (PLS), artificial neural networks (ANN), deep neural networks (DNN), and classification algorithms	Quantitative	369	chatbots	Bangladesh	VAM	'Perceived usefulness', 'perceived enjoyment', 'social influence', 'self-efficacy', and 'personal innovativeness' are the independent variables.	The identified dependent variables are study is 'attitude towards adopting ChatGPT' and 'intention to adopt ChatGPT'	No Explicit moderating variables identified
48	"The impact of pedagogical beliefs on the adoption of generative AI in higher education: predictive model from UTAUT2"	Julio Cabero-Almenara, Antonio Palacios-Rodríguez, María Isabel Loaiza-Aguirre, Paola Salomé Andrade-Abarca	2024	University Teachers (Professors)	Partial Least Squares (PLS-SEM), SmartPLS, Reliability tests (Cronbach's alpha, CR, AVE, Fornell-Larcker), Bootstrap t-test	Ex post facto, Quantitative, Structural Equation Modeling	425	Generative AI in Education (AIEd)	Private Technical University of Loja (UTPL), Ecuador	UTAUT2 with modifications (excluding price value & habit, including pedagogical beliefs)	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Pedagogical Beliefs (Constructivist & Transmissive)	Behavioral Intention, Attitude Toward Use	Pedagogical Beliefs (Constructivist vs. Transmissive)
50	"Students Level of Trust in the Use of AI Chatbots in Higher Education: A Quantitative Analysis Adopting	Arief Wicaksono; Farrel Izza Barunastra; Michael Chandra Jaya Giovani Suhari; Fredy Jingga	2024	Students	SEM	Quantitative	98	AI Chatbots	Indonesia	Extended TAM	Perceived Ease of Use ', 'Perceived Usefulness'	Attitude and Actual System Use	-

	Technology Acceptance Model"												
51	"Student Adoption of ChatGPT in Higher Education: A Technology Acceptance Model Survey"	Walatkiewicz, J., Al-Shorman, A., Darwish, O., & Carpenter, R.	2025	Students	Multiple Regression, Correlation	Quantitative	112	ChatGPT	USA	Extended TAM	Perceived Ease of Use ', 'Perceived Usefulness' & Technofobia	Behavioral Intention	-
52	"Factors that Influence College Students in the use of ChatGPT in Indonesia"	Silvano, R., & Gui, A.	2024	Students	SEM	Quantitative	331	ChatGPT	Indonesia	Modified UTAUT	Trust, PE, EE	Intension to use	-
53	"Adoption of generative AI in higher education: Understanding usage through a technology acceptance model"	Hanan Alotaibi, Asmaa Alayed	2025	Faculty Members	SEM	Quantitative	244	Gen AI	Saudi Arabia	Modified UTAUT	PE, EE, SI, FC	BI and UB	Gender and Academic Positions
54	"Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework"	Rana et al. 2024	2024	teachers, researchers, and students.	SEM	Quantitative	310	AI	Bangladesh	UTAUT with Trsut and Privacy	PE, EE, SI, FC with trust and Privacy	BI and UB	-

55	"Investigating EFL Students' Adoption of Generative Artificial Intelligence for English Learning through UTAUT2 and SDT: A Mixed-Methods Study"	Haryanto, S., Rahmatika, L., Islam, M. M., & Setiyoningsih, T.	2025	Students	SEM	Mixed Method	462	Gen AI	Indonesia	(UTAUT2) and self-determination theory (SDT)	PE, EE, SI, FC, PR, PC, HM, PA	BI and AU	-
56	"Examining the Acceptance and Use of AI-Based Assistive Technology Among University Students with Visual Disability:"	Alnajdi, S. M., Salem, M. A., & Elshaer, I. A.	2025	visually impaired undergraduates	SEM	Quantitative	395	AI-based assistive technologies (AIATs)	Saudi Arabia	(UTAUT) by incorporating physical self-esteem (PSE) as a moderator	PE, EE, SI, FC	BI and UB	Physical self-esteem (PSE)

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